

On the Importance of Super-Gaussian Speech Priors for Pre-Trained Speech Enhancement

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Abstract—For enhancing noisy signals, pre-trained single-channel speech enhancement schemes exploit prior knowledge about the shape of typical speech structures. This knowledge is obtained from training data for which methods from machine learning are used, e.g., Mixtures of Gaussians, nonnegative matrix factorization, and deep neural networks. If only speech envelopes are employed as prior speech knowledge, e.g., to meet requirements in terms of computational complexity and memory consumption, Wiener-like enhancement filters will not be able to reduce noise components between speech spectral harmonics. In this paper, we highlight the role of clean speech estimators that employ super-Gaussian speech priors in particular for pre-trained approaches when spectral envelope models are used. In the 2000s, such estimators have been considered by many researchers for improving non-trained enhancement schemes. However, while the benefit of super-Gaussian clean speech estimators in non-trained enhancement schemes is limited, we point out that these estimators make a much larger difference for enhancement schemes that employ pre-trained envelope models. We show that for such pre-trained enhancements schemes super-Gaussian estimators allow for a suppression of annoying residual noises which are not reduced using Gaussian filters such as the Wiener filter. As a consequence, considerable improvements in terms of Perceptual Evaluation of Speech Quality and segmental signal-to-noise ratios are achieved.

Index Terms—Super-Gaussian PDF, nonnegative matrix factorization, neural networks, speech enhancement.

I. INTRODUCTION

IN the presence of background noise, speech may be corrupted such that the perceived quality and possibly also the intelligibility are deteriorated. Similarly, also human-machine interaction, e.g., devices that employ automatic speech recognition systems to obtain an input from the user, may suffer from additional background noises. Hence, the enhancement of corrupted speech signals is an important task for many applications, e.g., in telecommunication, for speech recognition, and for hearing aids. In this paper, we consider methods that assume that the noisy speech signal has been captured by a single microphone.

Single-channel speech enhancement, has been a topic of research for decades and has given rise to many different approaches, e.g., [1]–[6]. Many approaches are formulated in the short-time Fourier transform (STFT) domain where a multiplicative gain function is applied to the complex

spectra to suppress the bands which mainly contain noise. Here, we distinguish two broad categories of enhancement schemes, namely *non-trained* and *pre-trained* enhancement schemes. Non-trained enhancement approaches, estimate the clean speech coefficients blindly from the noisy observation, i.e., the parameters of these methods are not learned from training data. For this, many different approaches have been proposed in the literature, e.g., [1], [3], [4], [7]–[11]. These methods often require an estimate of the speech power spectral density (PSD) and noise PSD which are also estimated blindly from the noisy observation, e.g., using [3], [5], [6], [12], [13]. These methods generally track the speech and the noise PSDs over time, i.e., a time-varying estimate is returned. Special attention has been turned to super-Gaussian clean speech estimators [1], [2], [7]–[10] as studies indicate that the complex Fourier coefficients are rather super-Gaussian than Gaussian distributed [14], [15].

In contrast to non-trained approaches, pre-trained approaches exploit information about the speech and possibly also about the noise signal which is learned prior to the processing. For this, various machine learning methods have been employed. In [16]–[20], generative models, e.g., hidden Markov models or mixtures of Gaussians, have been used to train the PSDs of speech and noise or related quantities. Approaches based on nonnegative matrix factorization (NMF), e.g., [21]–[26], represent speech and noise using a dictionary of nonnegative basis functions that are linearly combined to approximate the amplitude or the periodogram representations of speech and noise. Recently, also deep neural networks (DNNs) are investigated for speech enhancement. They have been employed in various ways, e.g., to estimate the noise PSDs [27], as classifier to identify appropriate speech PSDs [28], or to estimate spectral masks for the enhancement, e.g., [29]–[31].

Another way to categorize pre-trained enhancement schemes is the granularity of the pre-trained models. In [32], [33], a large inventory of prerecorded speech segments is used to resynthesize the clean speech signal. Similarly, overcomplete dictionaries, i.e., dictionaries having more elements than the actual dimensionality of the actual target have also been employed for NMF by exploiting sparsity, e.g., [34], [35]. Often, also DNN-based approaches employ large amounts of data and hidden layers to give an accurate representation of the spectral fine structure of the respective target signal [27], [30], [31]. Besides the enormous amount of data needed in training, the size of the model also leads to a high computational complexity and memory consumption. Contrarily in [16], [17],

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This work has partly been funded by the PhD program “Signals and Cognition”.

[19], [28], [36], the pre-trained speech models only represent the spectral envelope, i.e., harmonic structures caused by the vibrating vocal cords are not included. This increases the generalizability, reduces the computational complexity, and the amount of data required for training. However, the envelope representation also limits the quality of the enhanced signal as residual noise may remain, especially between spectral harmonics.

This contribution focuses on pre-trained enhancement schemes that employ spectral envelope models for speech. For reducing the residual noise between harmonics, different solutions have been proposed. In [19], a harmonic model has been used to attenuate the remaining noise component between harmonics. Contrarily, an estimate of the speech presence probability is employed in [28] to attain a suppression of the residual noise in non-speech areas. In this paper, we show that super-Gaussian speech priors have a similar effect if envelope models are employed in a pre-trained enhancement scheme to model speech. For this, we consider the super-Gaussian clean speech estimator proposed in [1]. The estimator is employed in a non-trained, a supervised NMF-based enhancement scheme based on [22], and a DNN-based scheme similar to [28]. We show that for the non-trained enhancement scheme which is capable of estimating the spectral fine structure of speech, the super-Gaussian speech model yields only small improvements. However, for the considered pre-trained enhancement schemes, where only an envelope model is employed, the super-Gaussian model has a very beneficial effect as it allows to remove annoying residual noises.

The paper is structured as follows. First, we recapitulate the clean speech estimator proposed in [1] in Section II. After that, we describe the considered pre-trained enhancement schemes in Section III and Section IV. The employed evaluation framework and training procedure are given in Section V. It is used in Section VI and Section VII where an analysis of the super-Gaussian estimator [1] and, respectively, a comparison of clean speech estimators employed in different enhancement schemes is presented. Finally, the conclusions are given in Section VIII.

II. SIGNAL MODEL AND SPEECH ESTIMATORS

In this section, we revisit the clean speech estimator [1]. This estimator is parameterized such that various known estimators, e.g., [3], [4], [7], [8], [10], result as special cases. In particular, it allows to incorporate super-Gaussian speech models and the estimation of compressed amplitudes. As in [37], we use the name (M)MSE estimation with (o)ptimizable (s)peech (m)odel and (i)nhomogeneous (e)rror criterion (MOSIE) for the estimator in [1].

MOSIE [1] is applied in the STFT domain. For this, the noisy input signal is split into overlapping frames and each frame is transformed to the Fourier domain after an analysis window has been applied. This yields the noisy spectra $Y_{k,\ell}$, where k denotes the frequency index and ℓ the frame index. It is assumed that the noisy coefficients $Y_{k,\ell}$ are given by

$$Y_{k,\ell} = S_{k,\ell} + N_{k,\ell}, \quad (1)$$

where $S_{k,\ell}$ and $N_{k,\ell}$ represent the clean speech and noise spectral coefficients, respectively. The estimate of the clean speech spectral coefficients $\hat{S}_{k,\ell}$ is obtained from the noisy observation $Y_{k,\ell}$ using MOSIE [1]. Afterwards, the estimated clean speech spectra $\hat{S}_{k,\ell}$ are transformed back to the time-domain and a synthesis-window is applied to the obtained time-domain frames. Finally, an overlap-add method is used to reconstruct the complete time-domain signal.

MOSIE [1] is a statistically optimal estimator in the sense of the mean-squared error (MSE). Such estimators consider the quantities in (1) as random variables, where the involved probability density functions (PDFs) are assumed to be known. Then, they find the estimate $\hat{S}_{k,\ell}$ that minimizes the MSE given by $\mathbb{E}\{|c(S_{k,\ell}) - c(\hat{S}_{k,\ell})|^2\}$. Here, $\mathbb{E}\{\cdot\}$ denotes the expectation operator and $c(\cdot)$ allows to incorporate perceptually motivated compression functions. Equivalently, the MSE optimal estimate of the clean speech coefficients $S_{k,\ell}$ can also be derived by solving [38, Section 5.2]

$$\hat{S}_{k,\ell} = c^{-1}(\mathbb{E}\{c(S_{k,\ell})|Y_{k,\ell}\}), \quad (2)$$

where $c^{-1}(\cdot)$ denotes the inverse of $c(\cdot)$. In general, the MSE optimal estimator of $S_{k,\ell}$ depends on the function $c(\cdot)$ and on the PDFs of the speech spectral coefficients $S_{k,\ell}$ and the noise spectral coefficients $N_{k,\ell}$.

For MOSIE [1], the complex speech coefficients $S_{k,\ell}$ are assumed to follow a parametrizable circular-symmetric possibly heavy-tailed super-Gaussian distribution. For this, the speech amplitude $A_{k,\ell}$ and speech phase $\Phi_{k,\ell}^s$ are treated separately, where $S_{k,\ell} = A_{k,\ell} \exp(j\Phi_{k,\ell}^s)$ and $j = \sqrt{-1}$. Accordingly, the amplitude of the speech coefficients $A_{k,\ell}$ is assumed to follow a χ -distribution as

$$f(A_{k,\ell}) = \frac{2}{\Gamma(\mu)} \left(\frac{\mu}{\Lambda_{k,\ell}^s} \right)^\mu A_{k,\ell}^{2\mu-1} \exp\left(-\frac{\mu A_{k,\ell}^2}{\Lambda_{k,\ell}^s}\right), \quad (3)$$

where $\Gamma(\cdot)$ denotes the Gamma function. Further, μ is the shape parameter and $\Lambda_{k,\ell}^s = \mathbb{E}\{|S_{k,\ell}|^2\}$ is the speech PSD. The case $\mu = 1$ is equivalent to the assumption that the complex speech coefficients $S_{k,\ell}$ follow a circular-symmetric Gaussian distribution. If $0 < \mu < 1$, (3) reflects the distribution of super-Gaussian distributed speech amplitudes $A_{k,\ell}$ and, hence, allows to describe complex super-Gaussian distributed coefficients $S_{k,\ell}$. The speech phase $\Phi_{k,\ell}^s$ is assumed to be uniformly distributed between $-\pi$ and π . This means that no prior knowledge about the phase is considered, which is often done in single-channel speech enhancement [3], [4], [10]. Approaches that include a non-uniform phase prior have been considered, e.g., in [2], [39], [40]. The complex noise coefficients $N_{k,\ell}$ are assumed to follow a circular-symmetric complex Gaussian distribution

$$f(N_{k,\ell}) = \frac{1}{\pi \Lambda_{k,\ell}^n} \exp\left(-\frac{|N_{k,\ell}|^2}{\Lambda_{k,\ell}^n}\right). \quad (4)$$

Here, the only parameter is the noise PSD $\Lambda_{k,\ell}^n$.

For MOSIE [1], $c(S_{k,\ell})$ is set to $c(S_{k,\ell}) = A_{k,\ell}^\beta$ where β is a compression factor. Due to the chosen $c(\cdot)$, this estimator yields only an estimate of the clean speech amplitudes $\hat{A}_{k,\ell}$.

TABLE I
LIST OF CLEAN SPEECH ESTIMATORS THAT MOSIE [1] GENERALIZES.

μ	β	Related estimator
1	1	STSA [3]
1	$\beta \rightarrow 0$	LSA [4]
$\mu < 1$	1	super-Gaussian amplitude estimator [8], [9]
$\mu < 1$	$\beta \rightarrow 0$	super-Gaussian LSA [10]

With the statistical assumptions given above, this estimate is given by [1]

$$\hat{A}_{k,\ell} = \sqrt{\frac{\Lambda_{k,\ell}^n \xi_{k,\ell}}{\xi_{k,\ell} + \mu}} \left[\frac{\Gamma(\mu + \beta/2)}{\Gamma(\mu)} \frac{\mathcal{M}(\mu + \beta/2, 1; \xi_{k,\ell})}{\mathcal{M}(\mu, 1; \xi_{k,\ell})} \right]^{\frac{1}{\beta}}. \quad (5)$$

Here, $\xi_{k,\ell} = \Lambda_{k,\ell}^s / \Lambda_{k,\ell}^n$ denotes the *a priori* signal-to-noise ratio (SNR) and $\zeta_{k,\ell}$ is given by $\gamma_{k,\ell} \xi_{k,\ell} / (\mu + \xi_{k,\ell})$ where $\gamma_{k,\ell} = |Y_{k,\ell}|^2 / \Lambda_{k,\ell}^n$ is the *a posteriori* SNR. The symbol $\mathcal{M}(\cdot, \cdot; \cdot)$ represents the confluent hypergeometric function. To obtain an estimate of the complex speech coefficients $\hat{S}_{k,\ell}$, the estimated amplitude in (5) is combined with the noisy phase $\Phi_{k,\ell}^y$ as $\hat{S}_{k,\ell} = \hat{A}_{k,\ell} \exp(j\Phi_{k,\ell}^y)$.

It is interesting to note that MOSIE [1], generalizes existing clean speech estimators. For example, if $\beta = 1$ and $\mu = 1$, MOSIE [1] is equivalent to Ephraim and Malah's short-term spectral amplitude estimator (STSA) [3] and, for very small values of β and $\mu = 1$, the log-spectral amplitude estimator (LSA) [4] is approximated. Table I gives an overview over the related estimators.

To evaluate the expression in (5), an estimate of the speech PSD $\Lambda_{k,\ell}^s$ and noise PSD $\Lambda_{k,\ell}^n$ is required. These can be obtained from non-trained speech PSD and noise PSD estimators, e.g., [3], [5], [6], [12] or using pre-trained approaches based on machine learning techniques as described next.

III. DNN-BASED SPEECH ENHANCEMENT SCHEME

The DNN-based enhancement scheme considered here is similar to the method proposed in [28]. The DNN is used to recognize a pre-defined set of phonemes. For this, the architecture in Fig. 1 is used. The features $\tilde{\mathbf{v}}_\ell' = [\tilde{v}_{1,\ell}', \dots, \tilde{v}_{\tilde{V}',\ell}']^T$ are extracted from the input signal, employed as the DNN's input and used to recognize which phoneme q was spoken at time frame ℓ . Here, $\tilde{v}_{i,\ell}'$ denote the elements of the feature vector $\tilde{\mathbf{v}}_\ell'$ which contains \tilde{V}' elements. Further, \cdot^T denotes the vector and matrix transpose. The features are passed through two hidden layers to finally obtain a score $f(q|\tilde{\mathbf{v}}_\ell')$ for each phoneme q . The scores $f(q|\tilde{\mathbf{v}}_\ell')$ are interpreted as the posterior probability that phoneme q was spoken given the features $\tilde{\mathbf{v}}_\ell'$. For the enhancement, the clean speech PSDs $\Lambda_k^{s|q}$ of the phonemes $q \in \{1, \dots, Q\}$ are trained before the processing takes place. For this, periodograms of labeled training data are averaged. These speech PSDs are used in MOSIE [1] to obtain a clean speech estimate $\hat{S}_{k,\ell}^{(q)}$ for each phoneme q . The estimates $\hat{S}_{k,\ell}^{(q)}$ are averaged based on the recognition scores $f(q|\tilde{\mathbf{v}}_\ell')$, i.e., the probability that phoneme q was spoken at time frame ℓ , to give a final estimate $\hat{S}_{k,\ell}$.

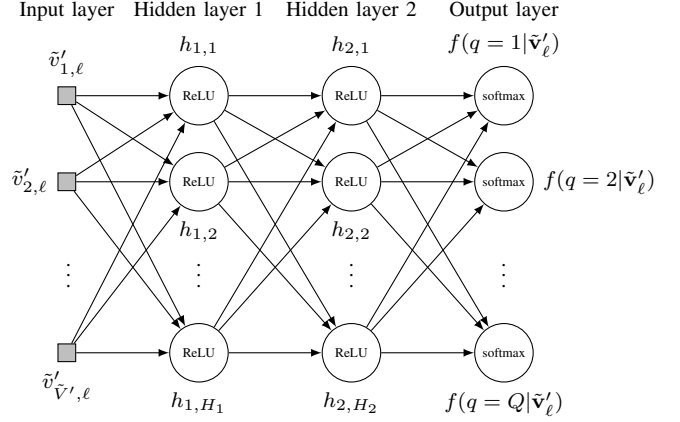


Fig. 1. Architecture of the employed DNN.

Similar to [28], [41], Mel-frequency cepstral coefficients (MFCCs) including their Δ and $\Delta\Delta$ accelerations are employed as features. The MFCC-vector is denoted by \mathbf{v}_ℓ and the number of elements of this vector is V . The features are extended by including temporal context information. For this, the features extracted from neighbouring frames are appended to the feature vector of the current frame as in [28], [41]. The stacked feature vector is given by

$$\tilde{\mathbf{v}}_\ell = [\mathbf{v}_{\ell-N}^T, \dots, \mathbf{v}_{\ell+N}^T]^T, \quad (6)$$

where N controls the amount of temporal context. Here, N is chosen such that a context of about 100 ms is considered. As in [28], the DNN is trained only using clean speech to ensure that the phoneme recognition does not depend on the background noise type. To improve the robustness of the recognition in noisy environments, the feature vectors are normalized using cepstral mean and variance normalization (CMVN) [42] before they are employed for training or testing [28]. Finally, the stacked and normalized feature vectors are denoted by $\tilde{\mathbf{v}}_\ell'$ and have the dimension $\tilde{V}' = (2N + 1)V$.

The hidden layers of the DNN consist of H_1 and H_2 outputs, respectively. Similar to [28], [41], [43], rectified linear units (ReLU) are employed as transfer functions of these two layers. Correspondingly, the outputs are given by

$$h_{1,j} = \max(0, \mathbf{w}_{1,j}^T \tilde{\mathbf{v}}_\ell' + u_{1,j}) \quad (7)$$

$$h_{2,j} = \max(0, \mathbf{w}_{2,j}^T \mathbf{h}_1 + u_{2,j}). \quad (8)$$

Concatenating the vectors $\mathbf{w}_{i,j}$ as $\mathbf{W}_i = [\mathbf{w}_{i,1}, \dots, \mathbf{w}_{i,H_i}]$, yields the weight matrices for the i th layer. Further, $u_{i,j}$ denotes the bias for the j th output of the i th layer. The vector \mathbf{h}_i pools the outputs of the i th hidden layer as $\mathbf{h}_i = [h_{i,1}, \dots, h_{i,H_i}]^T$. For the output layer, a softmax transfer function is used

$$f(q = j|\tilde{\mathbf{v}}_\ell') = \frac{\exp(\mathbf{w}_{3,j}^T \mathbf{h}_2 + u_{3,j})}{\sum_{j'} \exp(\mathbf{w}_{3,j'}^T \mathbf{h}_2 + u_{3,j'})} \quad (9)$$

which is interpreted as the posterior probability $f(q|\tilde{\mathbf{v}}_\ell')$ of the phoneme q .

The output of the softmax layer is used to combine the clean speech estimates $\hat{S}_{k,\ell}^{(q)}$ that are obtained for each phoneme q

Algorithm 1 DNN-based enhancement scheme.

Require: Trained DNN.

Require: Noisy observations $Y_{k,\ell}$ of a complete utterance.

- 1: Extract MFCCs \mathbf{v}_ℓ from $Y_{k,\ell}$ for complete utterance.
 - 2: Obtain $\tilde{\mathbf{v}}_\ell$ by stacking vectors as in (6).
 - 3: Apply CMVN over complete utterance to give $\tilde{\mathbf{v}}'_\ell$.
 - 4: **for all** frames ℓ **do**
 - 5: Estimate noise PSD $\hat{\Lambda}_{k,\ell}^n$ using [6].
 - 6: Obtain $f(q|\tilde{\mathbf{v}}'_\ell)$ from the DNN.
 - 7: **for all** phonemes q **do**
 - 8: Obtain clean speech estimate $\hat{S}_{k,\ell}^{(q)}$ for phoneme q .
 For this, $\Lambda_k^{s|q}$ and $\hat{\Lambda}_{k,\ell}^n$ are employed in (5).
 - 9: **end for**
 - 10: Obtain final clean speech estimate $\hat{S}_{k,\ell}$ using (10).
 - 11: **end for**
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by MOSIE [1]. More specifically, the clean speech coefficients are obtained by

$$\hat{S}_{k,\ell} = \sum_j^Q f(q = j|\tilde{\mathbf{v}}'_\ell) \hat{S}_{k,\ell}^{(q)}. \quad (10)$$

To evaluate the expressions for the clean speech estimators in (5), the spectral PSDs $\Lambda_k^{s|q}$ linked to each phoneme q are employed. The noise PSD $\Lambda_{k,\ell}^n$ is estimated using a non-trained noise PSD estimator. The steps required to enhance the noisy observations $Y_{k,\ell}$ using the DNN-based enhancement scheme are summarized in Algorithm 1. The parameters and the training methods used for this enhancement scheme are given in Section V-B.

IV. NMF-BASED SPEECH ENHANCEMENT SCHEME

In this part, the pre-trained enhancement scheme that is based on NMF is described. NMF approximates a nonnegative matrix \mathbf{Y} as $\mathbf{Y} \approx \mathbf{B}\mathbf{H}$. Here, \mathbf{B} and \mathbf{H} are also nonnegative matrices. The columns of \mathbf{B} are referred to as basis vectors and the columns of \mathbf{H} as activation vectors. NMF has been used for source separation, e.g., [21], [22], [34], and has also been applied to speech enhancement, e.g., [23]–[25].

Here, a simple supervised NMF approach is used which employs the Itakura-Saito (IS) divergence as cost function [22]. As argued in [22], if the noisy spectral coefficients $Y_{k,\ell}$ are independent and follow a circular-symmetric Gaussian distribution, minimizing the IS divergence for approximating the noisy periodogram as $[|Y_{k,\ell}|^2] = \mathbf{Y} \approx \mathbf{B}\mathbf{H}$ allows the elements of the product $\mathbf{B}\mathbf{H}$ to be interpreted as the noisy PSD $\Lambda_{k,\ell}^y$. For learning the basis matrices \mathbf{B} and activation matrices \mathbf{H} , the multiplicative updates rules in [22] can be used as

$$\mathbf{H} \leftarrow \mathbf{H} \odot \frac{\mathbf{B}^T \left((\mathbf{B}\mathbf{H})^{-2} \odot \mathbf{Y} \right)}{\mathbf{B}^T (\mathbf{B}\mathbf{H})^{-1}} \quad (11)$$

$$\mathbf{B} \leftarrow \mathbf{B} \odot \frac{\left((\mathbf{B}\mathbf{H})^{-2} \odot \mathbf{Y} \right) \mathbf{H}^T}{(\mathbf{B}\mathbf{H})^{-1} \mathbf{H}^T}. \quad (12)$$

The division and the power of the matrices are performed element-wise. Further, \odot denotes the element-wise multiplication of two matrices. After the application of (11) and (12), the columns of $\mathbf{B} = [b_{k,i}]$ are normalized such that $\sum_k b_{k,i} = 1$. The updates and the normalization are repeated until convergence.

The IS-based NMF is employed for estimating the clean speech PSD $\Lambda_{k,\ell}^s$ and the noise PSD $\Lambda_{k,\ell}^n$. Here, we use frame-stacking [26] similar to the DNN-based enhancement scheme to include temporal context information. The columns of the stacked matrix $\tilde{\mathbf{Y}} \approx \tilde{\mathbf{B}}\tilde{\mathbf{H}}$ are given by

$$\tilde{\mathbf{y}}_\ell = [\mathbf{y}_{\ell-N}^T, \mathbf{y}_{\ell-N+1}^T, \dots, \mathbf{y}_{\ell+N}^T]^T, \quad (13)$$

where \mathbf{y}_ℓ is defined as $\mathbf{y}_\ell = [|Y_{1,\ell}|^2, \dots, |Y_{K,\ell}|^2]^T$. Here, K denotes the number of Fourier coefficients. Again, N is chosen such that a temporal context of 100 ms is used. For estimating the speech and the noise PSD, it is assumed that the basis matrix $\tilde{\mathbf{B}}$ is given by the concatenation of a speech basis matrix $\tilde{\mathbf{B}}^{(s)}$ and a noise basis matrix $\tilde{\mathbf{B}}^{(n)}$ as $\tilde{\mathbf{B}} = [\tilde{\mathbf{B}}^{(s)}, \tilde{\mathbf{B}}^{(n)}]$. The speech and noise basis matrices are learned prior to the processing and are held fixed during processing. This means that only the activation matrices are updated using (11). For obtaining an estimate of $\Lambda_{k,\ell}^s$ and $\Lambda_{k,\ell}^n$, also the activation matrix $\tilde{\mathbf{H}}$ is split into a speech and noise dependent part as $\tilde{\mathbf{H}} = [(\tilde{\mathbf{H}}^{(s)})^T, (\tilde{\mathbf{H}}^{(n)})^T]^T$ such that $\tilde{\mathbf{Y}} \approx \tilde{\mathbf{B}}\tilde{\mathbf{H}} = [\tilde{\mathbf{B}}^{(s)}, \tilde{\mathbf{B}}^{(n)}][(\tilde{\mathbf{H}}^{(s)})^T, (\tilde{\mathbf{H}}^{(n)})^T]^T$. With this, the speech and the noise PSD can be obtained as

$$\hat{\Lambda}_{k,\ell}^s = \sum_{i=1}^{I^{(s)}} \tilde{b}_{\ell_0(k),i}^{(s)} \tilde{h}_{i,\ell}^{(s)} \quad (14)$$

$$\hat{\Lambda}_{k,\ell}^n = \sum_{i=1}^{I^{(n)}} \tilde{b}_{\ell_0(k),i}^{(n)} \tilde{h}_{i,\ell}^{(n)}, \quad (15)$$

where $I^{(s)}$ is the number of speech basis while $I^{(n)}$ denotes the number of noise bases. Further, $\tilde{b}_{k,i}^{(s)}$ and $\tilde{b}_{k,i}^{(n)}$ are the elements of the matrices $\tilde{\mathbf{B}}^{(s)}$ and $\tilde{\mathbf{B}}^{(n)}$, respectively. Similarly, $\tilde{h}_{i,\ell}^{(s)}$ and $\tilde{h}_{i,\ell}^{(n)}$ are the elements of the respective activation matrices. Finally, $\ell_0(\cdot)$ is a function that selects the elements in the stacked basis vectors that represent the current frame ℓ , e.g., the central elements in (13). The steps for enhancing the noisy observations are summarized in Algorithm 2. The employed parameters and the training procedures are clarified in Section V-B.

V. EVALUATION FRAMEWORK AND PARAMETERS

In this section, the evaluation framework, the training, as well as, the parameters employed for the non-trained and the pre-trained enhancement schemes are described.

A. Audio Material and STFT-Framework

For the analysis and evaluation, we employ speech material from the TIMIT database [44]. For the training of the DNN-based and the NMF-based enhancement schemes, we employ 1196 gender and phonetically balanced sentences from the TIMIT training set.

Algorithm 2 NMF-based enhancement scheme.

Require: Speech and noise basis matrix $\tilde{\mathbf{B}}^{(s)}, \tilde{\mathbf{B}}^{(n)}$.

- 1: Set $\tilde{\mathbf{B}} = [\tilde{\mathbf{B}}^{(s)}, \tilde{\mathbf{B}}^{(n)}]$.
 - 2: **for all** frames ℓ **do**
 - 3: Create stacked vector $\tilde{\mathbf{y}}_\ell$ as in (13).
 - 4: Initialize $\tilde{\mathbf{H}}$ with positive random numbers.
 - 5: **repeat**
 - 6: Update $\tilde{\mathbf{H}}$ as in (11).
 - 7: **until** convergence or maximum iterations reached
 - 8: **end for**
 - 9: Obtain $\hat{\Lambda}_{k,\ell}^s$ and $\hat{\Lambda}_{k,\ell}^n$ using (14) and (15).
 - 10: Use estimated PSDs in (5) to obtain $\hat{S}_{k,\ell}$.
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For experiments that require noisy data, we artificially corrupt sentences from the TIMIT test set [44] using various noise types. The types used in the evaluation are the babble noise, factory 1 noise, and pink noise taken from the NOISEX-92 database [45]. Further, we augment these noise types by an amplitude modulated version of the pink noise similar to [6] and a traffic noise taken from [46].

All signals have a sampling rate of 16 kHz or are resampled if necessary. Stereo signals are converted to mono by averaging the stereo channels. Further, the frame length of the STFT is set to 32 ms and an overlap of 50 % is employed. For the analysis and the synthesis a square-root Hann window is used.

B. Parameters and Training of the Enhancement Schemes

For the non-trained and the DNN-based enhancement scheme used in this evaluation, the noise PSD $\Lambda_{k,\ell}^n$ is estimated using [6]. The speech PSD of the non-trained enhancement scheme is estimated using temporal cepstrum smoothing as proposed in [5].

For the DNN-based enhancement scheme, 13 MFCCs are extracted for each frame of the input signal. Including the Δ and $\Delta\Delta$ accelerations, the unstacked vector \mathbf{v}_ℓ has a dimensionality of $V = 39$. The parameter N for the DNN is set to 3, i.e., the stacked feature vector $\tilde{\mathbf{v}}_\ell$ comprises 7 MFCC vectors \mathbf{v}_ℓ . Hence, the total feature dimensionality is $\tilde{V} = 273$. The two hidden layers have $H_1 = H_2 = 512$ output neurons which is similar to the approach in [28]. The CMVN is applied per utterance.

To determine the parameters of the DNN, i.e., the elements of the weight matrices \mathbf{W}_i with $i = 1, 2, 3$, the phoneme annotation given in the TIMIT database [44] is used. We distinguish between 61 different classes which include pauses and non-speech events. Correspondingly, the DNN-based recognizer distinguishes between these $Q = 61$ classes. The target vectors of the DNN are given by the annotation which is encoded in 61-dimensional vectors for each frame ℓ . For these vectors, all elements are zero except the q th element to indicate the respective phoneme. The error function is given by the cross-entropy which is minimized using scaled conjugate gradient back-propagation [47]. Before back-propagation, the weights of the DNN two hidden layers, i.e., \mathbf{W}_1 and \mathbf{W}_2 are initialized using the Glorot method [48]. The weights of

the output layer, i.e., \mathbf{W}_3 , are initialized using the Nguyen-Widrow method [49].

The speech PSDs $\Lambda_k^{s|q}$ that are linked to the phonemes q are trained as

$$\Lambda_k^{s|q} = \frac{1}{|\mathbb{L}(q)|} \sum_{\ell \in \mathbb{L}(q)} |S_{k,\ell}|^2, \quad (16)$$

where $\mathbb{L}(q)$ denotes the set that contains the frames that belong to the phoneme q in the training data. As (16) is scale-dependent, we normalize the time-domain clean speech input signal both in training and testing.

Also for the NMF-based enhancement scheme, we employ a context of 7 frames, i.e., N is set to 3. We use 30 bases in the speech basis matrix $\tilde{\mathbf{B}}^{(s)}$ and the noise basis matrix $\tilde{\mathbf{B}}^{(n)}$. For the training, a maximum of 200 iterations of (11) and (12) are performed. For $\tilde{\mathbf{B}}^{(s)}$, the same audio material used for the DNN-based approach is used. Separate basis matrices $\tilde{\mathbf{B}}^{(n)}$ are trained for each background noise considered in the evaluation, i.e., the noise types described in Section V-A. For this, two minutes of the respective noise type are used. This corresponds to a partitioning where 50 % of the background noise material is used for training and 50 % for testing. For testing, the noise matrix appropriate for the respective noise type is chosen in the evaluation, i.e., the background noise type is assumed to be known. For the updates of the activation matrix during testing, the maximum number iterations is set to 50 in Algorithm 2.

VI. ANALYSIS

In this section, we analyze the effect of the super-Gaussian speech estimators on non-trained and pre-trained speech enhancement schemes. Before that, we analyze how the shape μ and the compression β influence the behavior of MOSIE [1].

A. Analysis of the Gain Functions

In this part, we analyze the behavior of the clean speech estimator MOSIE [1]. For this, the gain function is considered which is defined as

$$G_{k,\ell} = \hat{S}_{k,\ell} / Y_{k,\ell} \quad (17)$$

$$= |\hat{S}_{k,\ell}| / |Y_{k,\ell}|. \quad (18)$$

The equality between (17) and (18) holds due to the fact that MOSIE [1] combines an estimate of the clean speech magnitude $\hat{A}_{k,\ell}$ with the noisy phase $\Phi_{k,\ell}^y$. Thus, the gain is a real function that describes by how much a spectral coefficient is boosted or attenuated depending on the speech PSD $\Lambda_{k,\ell}^s$, the noise PSD $\Lambda_{k,\ell}^n$, and the noisy input $Y_{k,\ell}$.

Fig. 2 shows the gain $G_{k,\ell}$ of MOSIE [1] for two *a priori* SNRs: $\xi_{k,\ell} = -5$ dB is shown in the upper row and $\xi_{k,\ell} = 10$ dB in the lower row. The compression parameter β is varied and the shape μ is kept fixed in the left panel and vice versa in the right panel. It is well known that super-Gaussian estimators ($\mu < 1$) preserve speech better than Gaussian estimators ($\mu = 1$) for large *a posteriori* SNRs [14]. However, in the context of pre-trained speech enhancement it is of particular interest that with decreasing shape μ , a stronger attenuation is applied to the input coefficients for low *a posteriori* SNRs $\gamma_{k,\ell}$ even if the *a priori* SNR $\xi_{k,\ell}$ is large. A similar effect is observed if a stronger compression, i.e., smaller values for β , is employed.

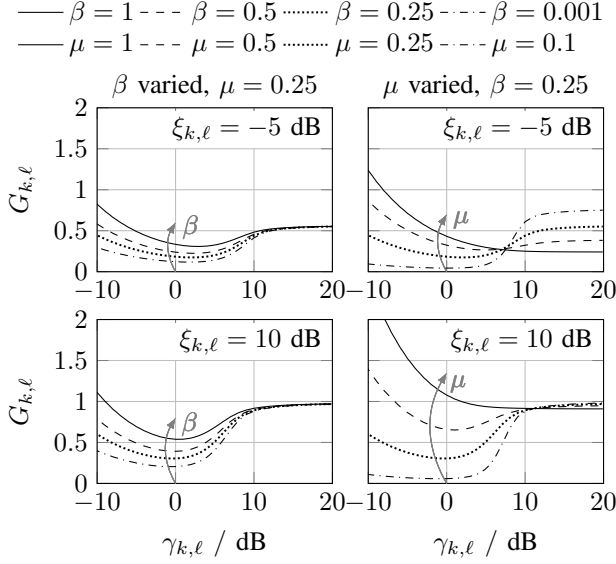


Fig. 2. Gain function $G_{k,l}$ of MOSIE [1] over the a posteriori SNR $\gamma_{k,l}$ for different values of shape μ and compression β . The upper row shows the results for an a priori SNR of -5 dB and the lower for an a priori SNR of 10 dB. See Table I for related estimators for the values of μ and β .

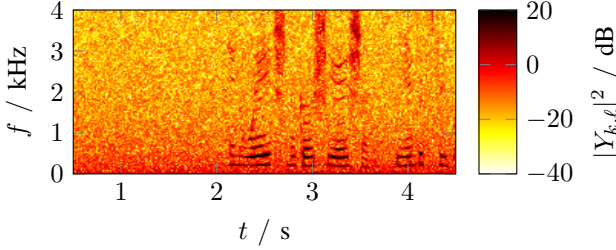


Fig. 3. Spectrogram of the example speech signal in stationary pink noise at 5 dB SNR. Here, f denotes frequency and t time.

B. Effects of Super-Gaussian Estimators on the Enhancement

In this part, we analyze how the behavior of MOSIE [1] influences the considered enhancement schemes. For this, a speech signal taken from the TIMIT test set is corrupted by stationary pink noise at an SNR of 5 dB. The spectrogram of the used signal is shown in Fig. 3. This signal is processed by the non-trained enhancement scheme and the two pre-trained enhancement schemes.

In Fig. 4, we depict the resulting a priori SNRs $\xi_{k,l}$. For the DNN-based enhancement scheme, the a priori SNR of the phoneme that is most likely to be present is shown for each frame. Note that this selection is only performed for the visualization in Fig. 4. Otherwise, $\hat{S}_{k,l}$ is estimated as in (10).

In Fig. 4, the estimated a priori SNRs $\xi_{k,l}$ obtained from the non-trained enhancement scheme shows a fine structure which is similar to the speech structure shown in Fig. 3. Contrarily, the structure of the a priori SNRs $\xi_{k,l}$ estimated by the pre-trained enhancement schemes is very coarse and reveals no or only little of the harmonic fine structure shown in Fig. 3. Using these envelopes models for the speech component, leads to an overestimation of the a priori SNRs $\xi_{k,l}$ between spectral harmonics. Additionally, the figure shows that only the non-

trained and the DNN-based enhancement scheme are able to assign low a priori SNRs $\xi_{k,l}$ to the segment where no speech is present. Contrarily, the NMF-based approach estimates the a priori SNR $\xi_{k,l}$ such that many frequency bins are close to 0 dB if only noise is present.

Next, the gain as defined in (17) is considered. For this example, we use MOSIE [1] with two different parameter setups. First, a setup is used where the clean speech coefficients $S_{k,l}$ are assumed to follow a complex circular-symmetric Gaussian distribution. For this, the parameters of MOSIE [1] are set to $\mu = 1$ and $\beta = 0.001$, which approximates the LSA [4]. For the second setup, the shape is reduced to $\mu = 0.2$, i.e., a super-Gaussian version of the previous estimator is employed. The gain is limited such that attenuations larger than 15 dB are prevented. The applied gains for the Gaussian and super-Gaussian case are shown in Fig. 5 and Fig. 6, respectively. Note that the gain function is clipped to 0 dB only in the visualization to make the plots easier to read.

Fig. 5 shows that the overestimations of the a priori SNR $\xi_{k,l}$, e.g., between spectral harmonics, result in a poor suppression for the pre-trained enhancement schemes when using a Gaussian estimator estimators ($\mu = 1$). The non-trained enhancement scheme is, however, not affected and achieves high suppression values between harmonics. This behavior can be explained from Fig. 2. For $\mu = 1$, the attenuation is mainly controlled by the a priori SNR $\xi_{k,l}$ where lower a priori SNRs $\xi_{k,l}$ lead to higher suppression values. From this it follows that an overestimation of $\xi_{k,l}$ results in lower attenuations as observed for the pre-trained enhancement schemes. As a consequence, using standard clean speech estimators, e.g., the LSA (see Table I), for pre-trained enhancement schemes that employ envelope models, results in audible artifacts.

Interestingly, Fig. 6 shows that the issues observed for $\mu = 1$ can be reduced if a super-Gaussian estimator ($\mu < 1$) is employed. In contrast to Fig. 5, the noise is suppressed between harmonics. Further, also higher attenuations are applied to the noise only segments. Considering Fig. 2, the behavior can be explained by the fact that lower shape values cause more suppression for low a posteriori SNRs $\gamma_{k,l}$. Hence, using super-Gaussian clean speech estimators, the background noise can be suppressed also when speech PSD envelopes from pre-trained approaches are employed.

VII. EVALUATION

Finally, we evaluate the performance of the different speech estimators using instrumental measures such as Perceptual Evaluation of Speech Quality (PESQ) improvement scores [50] and segmental SNR improvements [15], [51]. Additionally, the segmental speech SNR (SegSSNR) and the segmental noise reduction (SegNR) [15] are employed to quantify the speech distortions and noise suppression, respectively. Higher values for the SegSSNR indicate less speech distortion and higher values for the SegNR indicates more noise reduction.

For this evaluation, we use 128 sentences from the TIMIT core set. Again, it is ensured that the amount of audio material

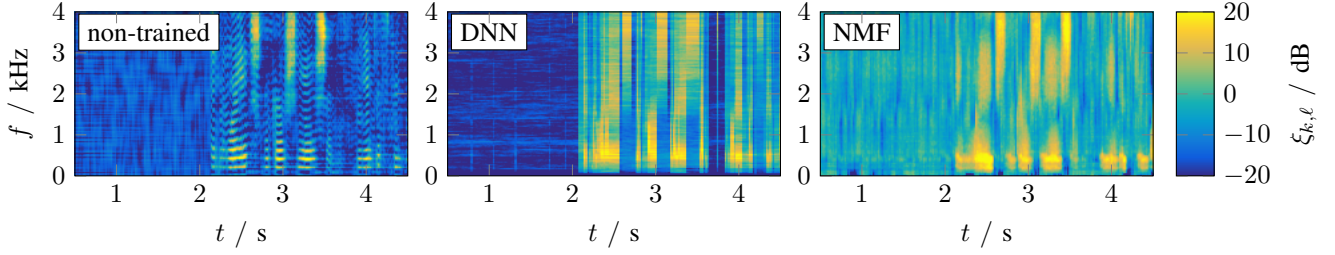


Fig. 4. *A priori* SNR $\xi_{k,\ell}$ estimated using different enhancement schemes for the excerpt shown in Fig. 3. Here, f denotes frequency and t time.

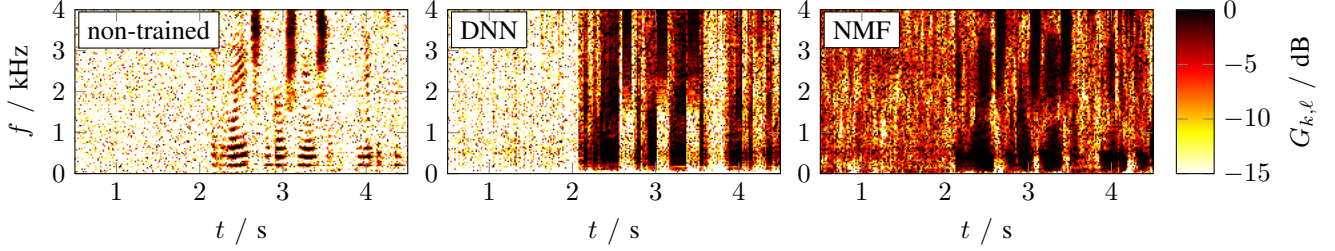


Fig. 5. Gain applied to the noisy input coefficients $Y_{k,\ell}$ by MOSIE [1] with $\mu = 1$ and $\beta = 0.001$ for different pre-trained enhancement schemes for the excerpt shown in Fig. 3. The parameter setup approximates the LSA proposed in [4] as shown in Table I. Here, f denotes frequency and t time.

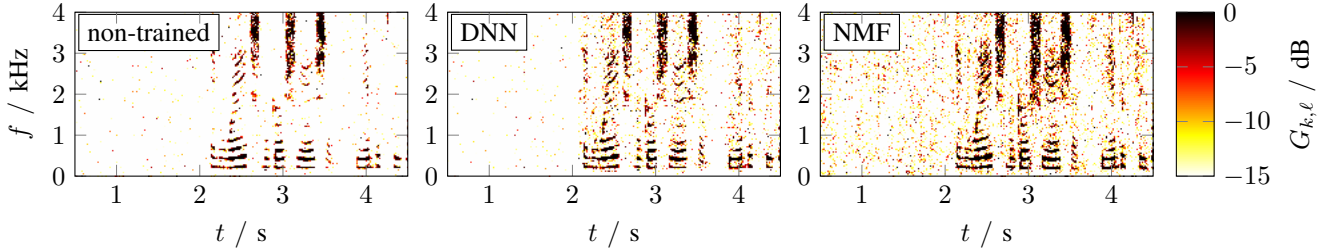


Fig. 6. Same as Fig. 5 but using $\mu = 0.2$ and $\beta = 0.001$ for MOSIE [1]. The parameter setup for MOSIE [1] approximates the super-Gaussian LSA proposed in [10] (see Table I).

is balanced between genders. The clean speech signals are artificially corrupted by the noise types described in Section VI at SNRs ranging from -5 dB to 20 dB. For each sentence, the segment of the noise signal where the speech signals are embedded in is randomly chosen. For the non-trained noise PSD estimator [6] used for the non-trained and the DNN-based enhancement scheme, a two second initialization period is included at the beginning of each noisy test signal. The instrumental measures, i.e., PESQ and the segmental SNR measures, are only evaluated in speech presence, i.e., after the two second initialization period. Similarly, also the SNRs used for the artificial mixing are determined based on the signal powers in speech presence. Further, the noise segments that were used for training the NMF-based enhancement scheme are excluded in the evaluation for all enhancement schemes, i.e., also for the non-trained and the DNN-based enhancement schemes. This is done to make the enhancement schemes more easily comparable. Similar to the analysis in Section VI, the gain of the clean speech estimators is forced to be larger than -15 dB.

A. Performance Impact of the Estimator Parameters

In this section, we analyze how the choice of the shape and the compression parameter influences the performance of clean speech estimators if used for the pre-trained enhancement schemes.

Fig. 7 shows PESQ improvement scores for MOSIE [1] as a function of the shape parameter μ and the compression parameter β . The graphs depict the average over all considered noise types and speech files for two different input SNRs. For the non-trained enhancement scheme, increasing super-Gaussianity ($\mu < 1$) and compression ($\beta < 1$) slightly improve the predicted speech quality PESQ. However, for the pre-trained enhancement schemes, increasing super-Gaussianity ($\mu < 1$) and compression ($\beta < 1$) improve the signal quality predicted by PESQ rather drastically. But there are limits. If μ and β are chosen too small, the quality may also degrade. This is most easily visible for the NMF-based enhancement scheme, if $\beta = 0.001$, $\mu = 0.2$ is compared to $\mu = 0.1$ and the same compression. For the latter, the PESQ scores are significantly lower.

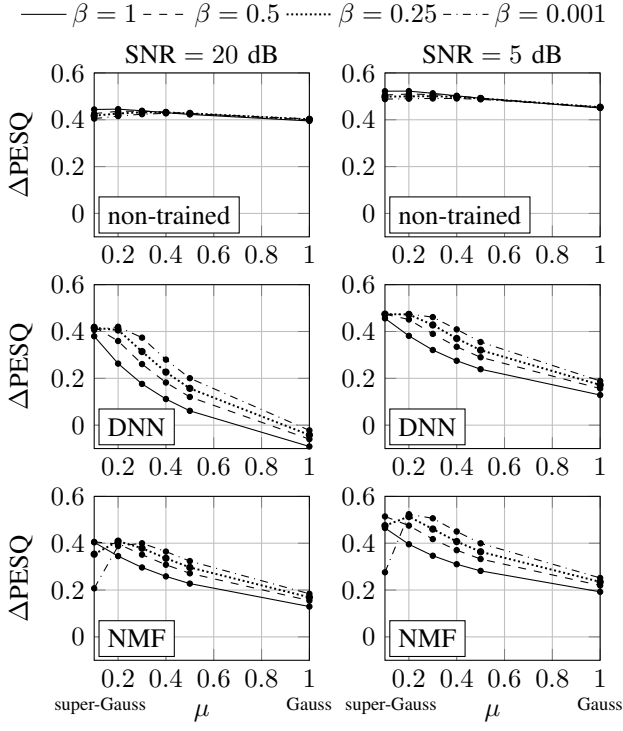


Fig. 7. PESQ improvement scores of MOSIE [1] for all considered enhancement schemes in dependence of the shape μ and compression β . For relations to other clean speech estimators, see Table I.

B. Comparison with Common Enhancement Schemes

In this final part of the evaluation section, we compare the super-Gaussian estimators, i.e., MOSIE [1] with standard approaches such as the Wiener filter, the STSA [3], and LSA [4]. To demonstrate that super-Gaussian estimators can improve the performance of pre-trained methods that use envelope models for speech, we use the following parameter settings for MOSIE [1]: $\beta = 0.001$ and $\mu = 0.2$. The parameters are chosen as a compromise such that all pre-trained enhancement schemes yield satisfying results.

Fig. 8 shows PESQ improvement scores and segmental SNR measures for the considered enhancement schemes. All enhancement schemes are evaluated using the previously mentioned clean speech estimators. The results again show that for the non-trained enhancement scheme, a super-Gaussian estimator only slightly improves the performance. Contrarily, the super-Gaussian setup for MOSIE [1] performs considerably better than the standard Gaussian clean speech estimator, i.e., the Wiener filter, the STSA [3] and the LSA [4], if the pre-trained estimators are considered. As shown in Section VI, the suppression of the standard approaches is mainly controlled by the *a priori* SNR resulting in low suppressions between harmonics for the pre-trained enhancement schemes. Here, this is reflected by the low segmental noise reduction values observed for the DNN-based and the NMF-based approach if standard clean speech estimators such as the STSA [3] or the LSA [4] are employed. However, for the super-Gaussian estimator MOSIE ($\mu = 0.2, \beta = 0.001$) the noise reduction is significantly increased and the residual noise, e.g., the

noise between harmonics, is reduced. This comes with a moderate increase in speech distortion as visible in a decrease in SegSSNR. Overall, the behavior of the super-Gaussian estimators, however, helps to improve the quality predicted by PESQ and to improve the segmental SNR.

VIII. CONCLUSIONS

In this paper, super-Gaussian clean speech estimators have been analyzed in the context of pre-trained speech enhancement algorithms that employ spectral envelope models for speech. In the analysis part, we showed that the usage of envelope models results in an overestimation of the *a priori* SNR, e.g., between spectral harmonics. As a consequence, using Gaussian estimators, noise between harmonic structures cannot be reduced such that residual noises remain after the enhancement. However, in this paper, we show that employing super-Gaussian clean speech estimators, such as MOSIE [1], leads to a reduction of the undesired residual noise. This interesting result stems from the higher attenuation that is applied by the super-Gaussian estimators if the *a posteriori* SNRs are low. This allows the estimators to implicitly compensate for the overestimated *a priori* SNRs without any further post-processing steps. As a consequence, for pre-trained enhancement schemes that use envelope models for speech, super-Gaussian estimators have a much larger effect on improving the enhancement performance than for non-trained enhancement schemes.

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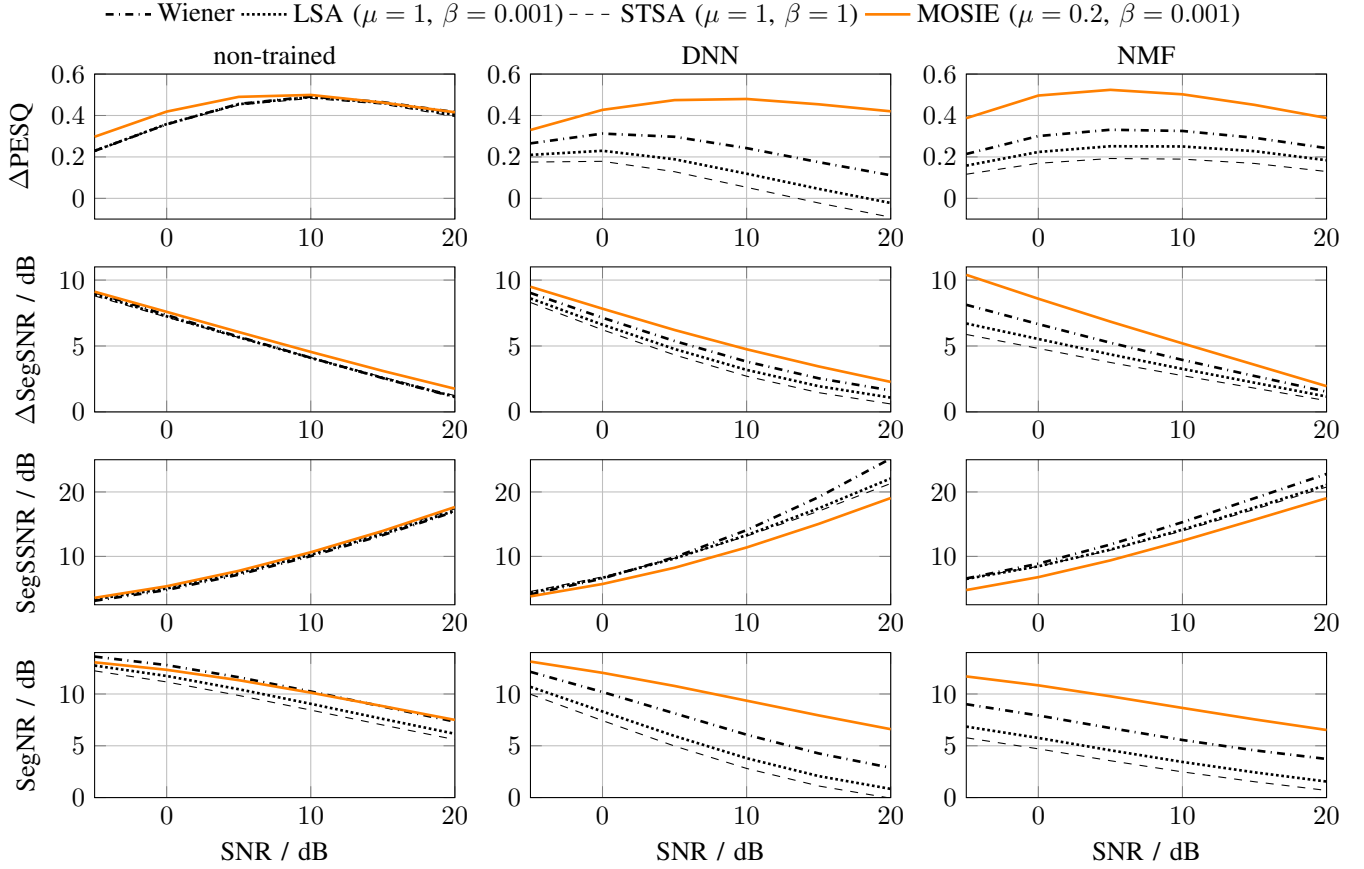


Fig. 8. PESQ improvement scores and segmental SNR measures for different clean speech estimators employed in the non-trained, the DNN-based, and the NMF-based enhancement scheme. While Wiener, LSA, and STSA employ Gaussian speech priors, MOSIE ($\mu = 0.2, \beta = 0.001$) represents a modern super-Gaussian speech estimator (see Table I).

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